AD-A083 973 COLORADO UNIV AT BOULDER INST FOR THE STUDY OF INTELL--ETC F/G 5/10
COMPREHENSION AND ANALYSIS OF INFORMATION IN TEXT. II DECISION --ETC(U)
DEC 79 E KOZMINSKY, W KINTSCH, P COREN N00014-78-C-0433

UNCLASSIFIED TR-89-ONR NL

1 OF 1
AD
A083973

END
DATE
FILMED
6-80
DTIC

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER
89-ONR

2. GOVT ACCESSION NO.
AD-A083 973

3. RECIPIENT'S CATALOG NUMBER

4. TITLE (and Subtitle)
(6) Comprehension and analysis of information in text. II. Decision making with texts.

5. TYPE OF REPORT & PERIOD COVERED
~~Occasional~~ report
7/1/79-11/30/79

6. PERFORMING ORG. REPORT NUMBER
ONR

7. AUTHOR(s)
(10) Ely Kozminsky, Walter Kintsch, Paul Coren
Lyle E. Bourne, Jr

8. CONTRACT OR GRANT NUMBER(s)
(15) N00014-78-C-0433

9. PERFORMING ORGANIZATION NAME AND ADDRESS
ISIB
University of Colorado
Boulder, Colorado 80309

10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
NR 157-422

11. CONTROLLING OFFICE NAME AND ADDRESS
Personnel and Training Research Programs
Office of Nval Research (Code 458)
Arlington, VA 22217

12. REPORT DATE
(11) December 1979

13. NUMBER OF PAGES
57 (12) 62

14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)
(14) TR-89-ONR-1

15. SECURITY CLASS. (of this report)
Unclassified

15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)
Approved for public release; distribution unlimited
(9) Technical rept. 1 Jul-30 Nov 79

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)
Reading, comprehension, memory, decision, concept learning

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Decision making based on information in texts was studied in a laboratory analogue of a complex, natural, information-analytic domain. Subjects acting as stock brokers acquired a conjunctive decision rule for predicting the market performance of a fictitious stock. Subjects read quarterly reports containing information on six market-information categories, of which only two were relevant to correct decisions. Decision performance differentiated between Learners (subjects who discovered the relevant

DD FORM 1473, 1 JAN 73 EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102-014-6601

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

411 401

JOB

20.

categories) and Nonlearners. Hypothesis selection behavior was similar to that reported with simpler concept learning problems. The category recall pattern reflected hypothesis selection, decision behavior, and subjects' overall category identification strategies. Further, these data were congruent with a model of text comprehension. Effective decision making in this task was viewed as the ability to acquire an appropriate control schema to guide comprehension and analysis of complex, often unreliable text inputs.

Comprehension and Analysis of Information in Text:

II. Decision Making with Texts

Ely Kozminsky, Walter Kintsch, Paul Coren and Lyle E. Bourne, Jr.

University of Colorado

Abstract

Decision making based on information in texts was studied in a laboratory analogue of a complex, natural, information-analytic domain. Subjects acting as stock brokers acquired a conjunctive decision rule for predicting the market performance of a fictitious stock. Subjects read quarterly reports containing information on six market-information categories, of which only two were relevant to correct decisions. Decision performance differentiated between Learners (subjects who discovered the relevant categories) and Nonlearners. Hypothesis selection behavior was similar to that reported with simpler concept learning problems. The category recall pattern reflected hypothesis selection, decision behavior, and subjects' overall category identification strategies. Further, these data were congruent with a model of text comprehension. Effective decision making in this task was viewed as the ability to acquire an appropriate control schema to guide comprehension and analysis of complex, often unreliable text inputs.

In semantically rich natural environments, human beings are continuously confronted with the necessity to analyze a complex informational input, to identify those elements pertinent to some predefined goal, and to decide on a basis on actions to attain their goals. A variety of familiar tasks exemplify this general process, ranging in complexity from political policy analysis to deciding which TV programs to watch. More often than not, information relevant to the decision task appears at least in part in text form. Further these texts characteristically are low in signal-to-noise (relevant-to-irrelevant information) ratio, riddled with redundancies, inexplicit, and sometning less than perfectly reliable. In many task domains, such as scientific research or intelligence analysis, the input is massive as well as imprecise. Yet for any goal-directed progress to be achieved, decisions must be made and executed on the basis of critical information derived from the input. It is the purpose of this paper to address, both empirically and theoretically, some of the issues inherent in this complex information-analytic process.

Our specific goal in the study to be reported was to develop and evaluate a simple theoretical model for analytic information processing in a laboratory analogue of one familiar natural domain, viz., stock market analysis. The model rests heavily on the concept of a <u>schema</u>. We view a schema as a

cognitive structure consisting of declarative and procedural information that can act, guide, or modify the information flow in a cognitive system. In this respect, our model is conventional, following the analysis of Rumelhart and Ortony (1977) among others. The main claim of the model is that the information analysis and acquisition is guided by a control schema. Thus, if some decision has to be made, the requirements of the decision task act as requests for particular pieces of decision-relevant information. The set of these requests, plus their interrelationships and mutual constraints, is the control schema. In the domain of this research, the operation of the control schema is determined by a person's knowledge about potential attributes that describe stock quality and interrelationships among those attributes, knowledge about methods or strategies of stock market analysis, and skills used in acquiring decision relevant information, i.e., reading, skills for scanning information in tables, etc.

The control schema, we suggest, controls both the information acquisition task and the decision itself. Thus, in this task we have two pertinent behavioral end points, decision behavior and comprehension, with which to evaluate the control schema and its operations on input material (in the present case, text). We propose to investigate comprehension processes through the medium of recall tests, employing a model of text comprehension developed by Kintsch and van Dijk (1978) which permits us to predict recall as a function of the control schema employed in comprehension. Techniques for the analysis of decision processes are not presently as well developed.

We have developed a laboratory task which, while simplified, preserves the salient features of real life information analysis. We deal with short, stereotyped texts and a simple decision rule. Though the textual information by its very nature is fuzzy, the decision rule is deterministic. Specifically, subjects will be asked to act as stockbrokers, who have to decide whether to buy the stock of some fictitious company after reading the "Quarterly Report" of that company. These reports are brief paragraphs which contain carefully prescaled information on six categories relevant to the market activity of the stock. Subjects are aware of these categories and are trained to evaluate the texts in terms of the information in these six categories. The decision rule which they have to infer inductively is a simple conjunction of two of (the six) categories. If the information in a text is positive in both categories, the stock will always go up in price, indicating a "buy" decision. The control schema that the subject has to acquire to perform this task is, therefore, a simple one, consisting of requests for evaluative information in each of the six categories, plus a designation of two of the categories as decision-relevant.

We have thus moved the natural problem close to a traditional concept learning paradigm, with certain obvious disadvantages but the possibly compensating advantage that we can employ the powerful behavioral analyses developed for that paradigm. Thus, in addition to the decision and recall data, we have subjects state their hypotheses about decision-relevant categories on each trial, and we obtain their evaluations of

the six categories on part of the trials. One can look at this experiment as a concept learning study with texts as input, and hence with a fuzzy, or uncertain, dimensional and value structure.

Text construction. Real stockmarket reports contain quite unsystematic information. They tend to be skimpy, fragmentary, variable in form, and often inconsistent. They typically communicate information only about a few characteristics of the stock (say, capitalization or earnings), which will differ from one report to another about the same company. For experimental purposes, we had to construct artificial reports. The details of this procedure are described in Kozminsky, Bourne and Kintsch (Note 1).

Briefly, we first identified six categories of information relevant to stock behavior from actual stockmarket reports. A larger number could, of course, have been identified, but the following six categories are common, representative and readily defined:

1) General information -- information about economic conditions within this country and across the world which may have a bearing on the market in general, but does not have direct application to a specific company.
2) Capitalization -- information concerning the financial position of a specific company (assets, liabilities, cash on hand, credit status, existing loans, etc.).
3) Growth prospects and productivity -- information concerning past growth, near-term and long-term

expectations, possible mergers, expansions, and new products.

4) Sales -- historical information on company sales, near-term and long-term expectations, sales comparisons with other companies within the industry.

5) Earnings and profitability -- past earnings, near-term and long-term expectations and comparsions with other companies.

6) Dividends -- past and anticipated payments to stockholders.

Our next step toward the construction of messages was to select from real stock market information individual sentences which seemed to us to fall clearly into one or another of these six categories. We were able to find many such sentences. Often a good sentence would contain information pertinent to two or more categories, in which case the sentence was modified so as to address mainly one.

Information contained in these sentences ranged from extremely positive, for example, "Dividends will be doubled in the next fiscal year," to extremely negative, for example, "Sales have struck an all time low in the first quarter." Through judicious selection and modification of the available sentences and several rating studies, we were able to develop a set of 20 sentences within each category which provided a uniform distribution of sentence values on a 5-point scale from extremely negative to extremely positive sentences.

These sentences were then combined into paragraphs containing information (positive or negative) on each of the six categories regarding a given company. Lists of six sentences, one of each category, were randomly selected and given to subjects who were asked to reorder the sentences in each list into the most rational (comprehensible, text-like) sequence. After reordering, subjects were asked to insert semantic connectives at their own discretion so that the ordered sentence lists made the best sense possible to them. A set of twenty texts, each providing information on every one of the six categories described above, was produced by this procedure. An example of such a text is given in Table 1. The first sentence contains information identifiable with the Dividends category. The second sentence is identified with capitalization, and so on. Notice that the sentences are not always unambiguous or explicit: For instance, the first sentence also refers to the financial position of the company--capitalization. In the second sentence the category identity is implicit. Thus, identifying the appropriate categories and evaluating them is a nontrivial task.

Insert Table 1 about here

Method

<u>Subjects</u>. Thirty-six subjects, 18 males and 18 females between the ages of 18 and 35 years participated in the experiment for five sessions each. They were paid $5.00 for their time, plus a bonus based on the quality of their performance in the experiment.

Materials. Subjects read 20 short texts each of about 100 words in length containing information relevant to six aspects of a fictitious company: General Factors, Capitalization, Growth, Sales, Earnings and Dividends. Each category of information in the text was pre-evaluated on a 5-point scale from 1 (negative) to 5 (positive information; see Kozminsky, Bourne, & Kintsch, Note 1). Unknown to the subject, two categories, Growth and Earnings, were chosen to be relevant to Buy/Not Buy decisions. The two relevant categories were combined according to a conjunctive rule to determine the proper decision on each trial. If the information for the two relevant categories in a text was evaluated 4 or more on a 5-point scale, the text was a positive example associated with a "Buy-stock" decision in anticipation that the stock price will go up. Ten positive texts (Buy) and ten negative texts (not Buy) were constructed. Three additional texts were prepared for use in a practice period.

Apparatus. The experiment was controlled by the Sigma 3 computer of the Computer Laboratory for Instruction in Psychological Research in the Department of Psychology, University of Colorado. The experimental program was written using the Display Terminal Experiment System (Spear, Note 2). The instructions and material was presented on a Four-Phase system CRT and responses were made on a five button panel interfaced with the computer.

Procedure. Experimental sessions were spaced over five consecutive days. The first session was a 90-minute training

session, and it was followed by four decision making sessions of approximately 30 minutes each. During the first training session, a subject went through the following sequence:

(a) The general nature of the task was explained. The subject was instructed to act as a stock broker recommending to a client to buy or not to buy a particular stock. In order to make a recommendation, the subject read a quarterly report about a company that issued the stock and made a recommendation according to the information in the report. For each correct recommendation the subject was paid 50 cents.

(b) A detailed description of the six informational categories was given.

(c) Then 18 sentences from the practice texts were displayed one at a time and the subject learned, with feedback, to assign sentences to their corresponding categories.

(d) In a second pass with the same 18 sentences, the subject evaluated the information in each sentence on the 5-point scale again with feedback.

(e) The nature of the decision rule, a conjunction, was explained and demonstrated with the three practice texts.

(f) Finally, a background description of the company in question was presented and followed by a short comprehension test.

The 20 texts were divided into four blocks, 5 texts in a block. In each of the four decision sessions a subject read five reports. Each subject was assigned to one of four

groups in which the text blocks were sequenced in counter-balanced design.

The decision sequence for each text was as follows:

(a) The subject selected two categories for a hypothesis about the relevant categories and marked them on a decision record. The decision record was in front of the subject throughout the experiment and he or she was allowed to examine it ad lib.

(b) The subject read the text and made a buy/not buy decision according to his or her expectation that a stock price will go up or down.

(c) Confidence in the decision was rated on a 5-point scale.

(d) Feedback about the decision was given and the subject recorded the outcome, right or wrong, on the decision record.

(e) The subject reinspected the text in order to decide whether and how to modify the hypothesis.

Subjects were told that they would, on occasion, be asked to recall the text just read. In instructions prior to the decision sessions, subjects were encouraged to recall as much as they could, not necessarily verbatim, and were told that for satisfactory recall they would get an additional bonus of $2.50 at the end of the experiment. (All subjects received this bonus.) These recall probes were given twice in each session immediately after the subject made a decision. Recall was not time limited. After recall, the subject evaluated the six informational categories in the text on a 5-point scale.

Then the sequence continued as in no recall trials. In each session the first trial and one other at random contained a recall test, a total of eight recall tests.

After the last decision session the subject received two final tasks, first, assigning sentences from four texts, to categories and, second, evaluating the informational content of these sentences. Also, a questionnaire was administered about the subjects' background, their attitude toward the experiment, and a verbal description of their decision behavior.

Results

There are three distinct sources of data in this experiment: (a) the hypothesis selection and decision data which were obtained on all trials of the experiment, (b) free recall protocols from some of the experimental trials, and (c) questionnaire data after the end of the experiment proper. We shall discuss these three data sources separately, emphasizing their interrelationships whenever possible. The decision and hypothesis selection results pertain to such questions as: How well did subject learn? What differences characterize the behavior of those subjects who did versus those who did not find a solution? The recall data are of interest because they permit one to infer what sort of information subjects had available when they made their decisions. Finally, the questionnaire data allow us to distinguish between problem solving strategies and to relate these strategies to characteristics of the decision processes as well as to the nature of the subjects' recall.

Hypothesis and decisions

Throughout this presentation we will distinguish between two subject groups: Learners are those subjects who, on some trial before the end of the experiment, selected the relevant categories Growth and Earnings as their hypothesis and maintained that hypothesis until the end of the experiment; The remaining subjects are grouped as Nonlearners. This criterion was used in preference to one based on decision performance because the uncertainty in the stimuli (texts) insured some proportion of decision error. On this criterion, 19 subjects were identified as learners and 17 as nonlearners. The mean of the first post-learning trial was 10.79 (approximately at the beginning of the third session), SD = 6.29. The distributions of trial numbers on which a relevant category was identified and maintained are shown in Figure 1.

Insert Figure 1 about here

When the subjects were asked, after the end of the experiment, to rate each category on a 10-point scale for its relevance to the decision task, learners rated the relevant categories higher than irrelevant categories by 6.55 points, while nonlearners produced only a 2.53 point difference between relevant and irrelevant categories. This difference between learners and nonlearners is statistically reliable, $t(34)=4.71$.[1] Thus, the questionnaire results support the distinction between learners and nonlearners on the basis of intra-experimental hypothesis statements.

Decision performance. The proportions of correct decisions for learners and nonlearners over trials are shown in Figure 2. Average nonlearner performance was 53% correct, not reliably different from chance. Average learner performance was significantly better than chance, $t(18)=3.42$. An analysis of variance with the factors learners vs. nonlearners, presentation order of the texts, and sessions yielded a significant F value for presentation order, $F(3,84)=7.38$, and a marginally significant interaction between learners and nonlearners over sessions, $F(3,84)=2.42$, $p \leq .10$. When the confidence ratings for the decisions were included in the analysis, this interaction reached a conventional significance level, $F(3,84)=3.38$.

Insert figure 2 about here

A comparison of pre- and postsolution decision performance for learners with the decisions made by nonlearners during the first and second half of the experimental sessions is presented in Table 2. While learners improve after they have decided upon the right hypothesis, nonlearners remain at a chance level. This interaction is highly significant statistically, $F(1,34)=10.90$.

Insert Table 2 about here

The evidence, then, is fairly clear: those 19 subjects classified as learners did indeed learn something about the appropriate decision rule, while the 17 nonlearners did not. It is important to note that this does not reflect an inability

of the nonlearners to understand the textual materials. After the end of the experiment-proper, all subjects were asked to classify and rate the sentences from four experimental texts. Learners and nonlearners agreed equally well as to whether the sentences were positive or negative (82% versus 80% correct, $\underline{t}(35)=.70$), and learners were only slightly more accurate in identifying the category to which each sentence belonged (92% correct versus 86%, $\underline{t}(35)=1.84$). Thus, the groups were equivalent in their potential to learn. What, then, did the learners do differently from the nonlearners?

Hypothesis selection. Subjects were requested to record at the beginning of each trial their hypothesis about the two relevant categories. The decisions they made were in general consistent with their stated hypotheses, 92% of the trials for learners, and 88% of the trials for the nonlearners, the difference being statistically unreliable, $\underline{t}(35)=.77$. However, there were learner vs. nonlearner differences in a number of other statistics that have been used in concept formation experiments employing nonverbal stimuli and deterministic rules (e.g., Millward & Spoehr, 1973). Some of the more pertinent hypothesis selection characteristics are summarized in Table 3 for presolution trials.

Insert Table 3 about here

(a) The likelihood of hypothesis change. Learners and nonlearners did not differ in their hypothesis change rate. For both groups the change rate dropped from about one hypothesis

change every two trials in the first half of presolution trials to about one change every three trials in the second half, $F(1,30)=15.90$. Relative to problems with simple structure this rate is low. We suspect that subjects in this study adjusted their hypothesis change rate by taking into account the uncertainty about properly categorizing and evaluating the information in the text.

(b) Category changes per hypothesis change. This measure decreased significantly from the first to the second half of the presolution trials, $F(1,29)=11.20$. There was however, a significant interaction, $F(1,29)=4.40$; when changing their hypothesis, learners consider more categories than nonlearners during the first half presolution trials.

(c) Proportion of incorrect decisions in a hypothesis run. Learners tolerated a ratio of about two incorrect decisions to every one correct before changing their hypothesis. For nonlearners this ratio was lower in the first half trials but not significantly so, $F(1,30)=2.44$. This measure is complementary to (a) and indicates the degree of adjustment to the uncertainty in the task. It also indicates tolerance to errors that can occur upon incorrect category perception.

(d) The likelihood of changing a hypothesis after an error. On the average, subjects changed their hypothesis only on 79% of the trials on which they had been told that their Buy/No Buy decision was incorrect, probably reflecting the fact that they were somewhat uncertain as to whether they had interpreted the information in the text correctly. However, the subjects' readiness to change after an error increased

sharply during the presolution trials, $F(1,30)=8.46$, with learners always being more likely to change than nonlearners, $F(1,30)=4.20$. Thus, learners were more successful in eliminating false hypotheses.

(e) Hypothesis recurrencies. Learners were significantly less likely to try out a hypothesis again that had already been contraindicated, $F(1,27)=4.24$.

(f) Trials before a hypothesis is reconsidered. The better memory of learners for what they had done before is apparent from the fact that they waited significantly longer than nonlearners before they reconsidered an already-tried hypothesis, $F(1,24)=8.56$

In summary, these analyses highlight the following differences between learners and nonlearners. First, learners adopted a more global approach to this problem initially, considering more categories of information as potentially relevant during early trials (reports). Both groups adjusted their hypothesis change rate to the uncertainty in the task, but learners were more systematic and more conservative in the actual changes made. Furthermore, learners were more sensitive to the implications of feedback regarding their decisions, making more appropriate changes and only on occasions dictated by feedback. Finally, learners were less likely to retest hypotheses eliminated by information provided on earlier trials; which implies more confidence in previous decisions, better memory, or a more effective problem solving strategy. This summary bears remarkable similarity to conclusions about

good and bad problem solvers in vastly different and simpler problem domains (e.g., Bourne, 1965; Millward & Spoehr, 1973). Our results may, therefore, be taken to suggest the existence of much the same basic processes underlying a wide range of comprehension-abstraction-decision behaviors.

Recall

In every one of the four sessions of the experiment subjects were asked to recall two of the texts immediately after they read them and made their decisions. In each session the first text and one other randomly selected text were recalled. Each one of the eight recalled texts was propositionalized using the method developed by Kintsch (1974). Then, each recall protocol was scored by template matching it to the propositional test base (see Turner and Greene, (1978) for details of this procedure). As a further measure of comprehension, reading times were obtained for all texts.

There were no differences between learners (33.90% recall) and nonlearners (34.26% recall) in amount recalled (i.e., number of propositions). In an analysis of variance with the factors learners-nonlearners, sessions, first- and second-recalled text in each session, and presentation blocks, only the main effects of session, first-vs-second recall test within sessions, and blocks were significant. Recall improved over the four experimental sessions, from 27.52% in the first session, to 34.50%, 36.81%, and 37.51% in the following sessions, $\underline{F}(3,84)=6.49$. The first text in each session yielded significantly

higher scores than the second text, 36.45% vs. 31.72%, $F(1,28)=15.88$. Blocks were also significant statistically, $F(3,84)=10.06$, indicating a lack of homogeneity among the texts used in the experiment.

Further, learners and nonlearners did not differ in reading rate, where a corresponding analysis yielded only two significant interactions, between first-and-second test and sessions, and first-and-second test and blocks, $F(3,84)=4.06$ and $F(3,84)=12.38$, respectively. These merely indicate the expected variability among texts in the various presentation blocks, but also question the usefulness of the second test in each session on which reading rates first decreased and then increased over sessions. The difference of primary interest, between learners and nonlearners, is simply not present. Indeed, reading rates are almost identical: 3.13 seconds per proposition for learners, and 3.15 seconds per proposition for nonlearners. (Seconds per propositions rather than total reading times were used to control for the differences in the lengths among the experimental texts.)

There are, however, differences between learners and nonlearners if one takes into account the nature of their recall, rather than merely the overall amount. Learners remember those aspects of the texts that are relevant to the decision task, while nonlearners do not show a comparable selectivity and appear more text-bound than goal-determined. Suppose one asks whether, for each of the six task dimensions, a subject recalled enough information to permit a correct evaluation on that dimension

(i.e., whether the dimension is positive or negative). Since the various dimensions differ greatly in their saliency depending upon the particular text that happens to be used, the scores from the first time each text was used (when the subjects as yet knew nothing about the decision task) were subtracted from all scores. Thus, evaluative memory improvement scores are obtained. On the average, these were higher for learners (.47) than for nonlearners (.02), $F(1,31)=4.12$, $p=.052$. Similarly, when they were asked, at the end of each recall trial, to rate the six critical task dimensions as to their positive or negative informational values, learners showed considerable improvement during the course of the experiment, from 66% correct on presolution trials to 79% after they had found the correct solution. Nonlearners, on the other hand, gave only 63% correct evaluations over the entire experimental task. (Note learners achieved 82% correct and nonlearners 80% when rating the same sentences outside the decision task context).

The selectivity of recall by learners is most clearly demonstrated in Figure 3, which plots percent recall for the relevant categories Growth and Earnings. Again, improvement over the first trial recall is shown rather than raw scores in order to control for saliency effects. The data are averaged by aligning scores, such that for each subject the trial on which a correct hypothesis was formed corresponds to the first postsolution trial. Subjects who never learned contribute only to the presolution portion of the learning curve.

Figure 3 shows that as learning proceeded, subjects recalled increasingly more from the relevant dimensions, and significantly more once they had the correct solution. (The final drop in the curve is based on a small number of scores and is therefore difficult to interpret.) The gradual improvement on presolution trials and the high level of recall of the relevant dimensions thereafter might be an artifact of the general increase in recall over sessions. Figure 4 shows, however, that this improvement was mainly due to the better recall of the relevant information by those subjects who learned the proper decision rule, confirming the interpretation of Figure 3 as a selection process on relevant text information.

Insert figures 3 and 4 about here

Since total recall was the same for learners and nonlearners, while learners recalled more relevant information than nonlearners, the latter must have recalled relatively more task-irrelevant information from the experimental texts. This is particularly true for one type of easily identifiable irrelevant information, namely, the sentence connectives that were inserted into the experimental paragraphs to make them appear more like real texts than lists of sentences. For connective recall (improvement over the first time a text was read in order to control for differential saliency effects), the scores for nonlearners are four times as high as those for learners, 16.65% and 3.97% respectively, $\underline{F}(1,31)=3.48$.

<u>A recall model</u>. Learners retain relevant information, while nonlearners show little selectivity. A rather simple

explanation of this difference follows from the model for text comprehension and recall proposed by Kintsch and van Dijk (1978). According to that model, people remember what they do. Reading the experimental paragraphs leaves certain kinds of memory traces. Evaluation of six task categories has its own further memorial consequences. All subjects undertake these activities, but only the learners consistently select the categories of Growth and Earnings as relevant and base their decisions upon their evaluation of these categories. This fact, we propose, leads to the recall enhancement on postsolution trials shown in Figure 3.

Theoretically, we assume that the basic local processes in reading (that is, the microprocesses) are the same for all subjects, but that there are two kinds of macroprocesses. One is common to all subjects and is controlled by the instruction to rate and evaluate all six task dimensions within each text. This process leads to the selection of evaluation-relevant information for each category. In this task, then, the "gist" of each paragraph consists of the six category evaluations, and the information used in arriving at these evaluations is presumed to have a special status in memory (as macropropositions). But, in addition, for learners only, higher level macropropositions can be identified on postsolution trials, namely the decision-relevant evaluations. Thus, as far as memory is concerned, we need to distinguish between micropropositions, and two kinds of macropropositions, those for the relevant and those for the irrelevant categories.

Consider how this model fits the recall data in the present experiment. Because we are interested in studying the effects of mastering the decision task on recall, we shall examine first the data from Sessions 3 and 4, when at least some subjects were making correct decisions. Only the first recall in each session was used for model fitting, because the second recall was significantly lower and might lead to distortion in the parameter estimates. Thus, there were four different texts to work with. For each of these, Growth and Earnings were the relevant categories. For these two categories a subject's data were included in the analysis only if these categories were indeed selected (hypothesized) as relevant by that subject. For the other four categories, a complementary selection was made: a subject's data in any one of these categories were considered only if the category was not the subject's hypothesis on that trial. Thus, not all data were used in the model analysis: for the relevant categories, we looked at only those subjects who thought these categories in fact were relevant, and for the irrelevant categories we took only those subjects who thought them irrelevant. Under these circumstances, unambiguous theoretical predictions were possible. However, we had only 314 protocols points to work with (70 were deleted for the reasons explained), which is not sufficient to support sophisticated statistical estimation procedures.

Detailed descriptions of the model are available in Kintsch and van Dijk (1978). Here, we shall merely sketch the main features of the model by working through a small example.

The model accepts as input a proposition list that represents the semantic context of the text. This list is obtained through handcoding the actual text according to a set of semi-explicit rules. The model attempts to simulate the organizational processes that this semantic input undergoes during comprehension, distinguishing their local (microprocesses) and global (macroprocesses) components. The model reads a text (or, rather, the corresponding proposition list) in chunks, tries to determine the coherence of the information in each chunk, and relates the various chunks via common referents carried over from one chunk to the next in a limited capacity buffer. Recall predictions follow from this model because each time a proposition is processed, it may be stored in memory (and later retrieved on the recall test) with some probability $\underline{p}$, to be estimated from the data. Each proposition is processed at least once upon input, but some propositions are processed more frequently because they are held over from one processing cycle to the next in the short-term buffer.

The macroprocesses occur under the control of the decision schema. The purpose of reading these texts is to identify and to evaluate the six informational categories. Hence, all propositions that are directly relevant to this operation receive further processing and are stored in memory with some probability $\underline{m}$, another parameter of the model. Finally, the two categories upon which the actual decision is based are processed once more, the memorial consequences of which is represented by a third model parameter, $\underline{n}$.

Insert Table 4 about here

As an example, Table 4 shows how the fourth sentence from the text from Table 1 is processed by the model. First of all, since it is longer than 21 words, the sentence is broken into two chunks for processing. Propositions P37, P39, and P42 are selected as macrostructure-relevant, because they are needed to infer the identity of the category--Earnings--and whether the information about Earnings in this text is positive or negative. Since Earnings, furthermore, is a category upon which a decision is actually made, these propositions are processed twice at the macrolevel, indicated by the operators M and M in Table 4. Most macropropositions are selected on the basis of a key-word approach in the present texts (e.g. "Earnings", "Dividends"); where this approach fails, normal conditions or consequences for any of the six text categories are determined from which evaluative statements can be inferred. The macroprocesses also provide a superordinate proposition for the more local processing of the text, in this case P39. The microprocesses then attempt to construct a coherent text base around this superordinate, by connecting all propositions to it in a tree-like structure as shown in Table 4.[2] Connections are made whenever two propositions share a common referent; when this condition does not obtain, bridging links must be inferred. Once a text base is constructed, there are rules in the theory to select a few propositions to be held over for the next processing cycle so that a single coherent structure is generated rather than a separate tree for each processing cycle. The

propositions to be held over are selected on the basis of their superordinate position in the text base as well as their recency. In the present example, P37 and P39 are held over, and the input propositions from the next cycle are directly annexed to them, resulting in a coherent representation for our sample sentence. The memorial effects of these microprocesses are indicated by the operator S in Table 4 (e.g. the S-operator is applied twice to P37 because that proposition was processed in both processing cycles).

In the model, the S, M and N operators are simple probabilistic equations with three parameters, $\underline{p}$, $\underline{m}$ and $\underline{n}$. These can be estimated by fitting the actual pattern of recall to the theoretical predictions. In the present case, a version of the method of moments was used for estimating these parameters, and other parameters of the model, such as the input size which we set at 21 words, or the buffer capacity, s=2, were simply guesses that appeared reasonable from other experience with this model. (As noted, more data would be needed for the use of more sophisticated statistical procedures.) However, even with these nonoptimal estimates, the resulting recall predictions appear to mirror reasonably well the main trends in the data in Table 4. Indeed, over all four texts, the predictions are excellent. Table 5 shows the $\underline{p}$, $\underline{n}$ and $\underline{m}$ parameters that were estimated for the four texts, the goodness of fit of the model to the data in terms of a chi-square criterion, and the correlation between observed and predicted recall patterns. The average correlation of .84 is comparable with other

applications of the model (e.g. Kintsch & van Dijk, 1978; Spilich, Chiesi, Vesonder, & Voss, 1979). Note that for two of the paragraphs, our estimate of *n*, which represents the effects of actually making a decision on the two relevant categories Growth and Earnings, turned out to be zero; 20 learning trials were apparently not sufficient to produce strong selection effects in all of the texts.

The good fit of the model to the recall data is important because it provides converging evidence for the theoretical claim that mastering the decision task involves the acquisition of a control schema. In its crudest form, this schema consists of six independent requests for evaluative information about each of the experimental categories, plus a (conjunctive) decision rule. What we have shown now is that this same schema also controls the subjects' recall. We still need to investigate the relationship between what is remembered and the particular hypotheses that a subject selects for the decision task, especially with respect to strategy differences. Do learners somehow use their memory differently than nonlearners?

Insert Table 5 about here

Memory and hypothesis selection. Given that a subject changed his hypothesis on Trial *i* and that he recalled a text on that trial, each category state was determined relative to the subject's hypothesis on Trial *i*-1. There are four possible category state transitions: Kept. A category was in the subject's hypothesis on Trial *i*-1 and it was maintained in the subject's hypothesis on Trial *i*. Nonselected. A category

was not in subjects hypothesis on Trial _i_-1 and it was not selected to be in the hypothesis set on Trial _i_. Selected. A category was not in the hypothesis set on Trial _i_-1 and it entered the set on Trial _i_. Dropped. A category was in subject's hypothesis on Trial _i_-1 and it was dropped from the set on Trial _i_.

As an example, suppose that the hypothesis set on Trial _i_-1 consisted of the categories Capitalization and Dividends and that on Trial _i_ the set was composed of Capitalization and Earnings. In this case, the category Capitalization was kept from Trial _i_-1 to Trial _i_; the categories General Factors, Growth, and Sales were nonselected; Earnings was selected; and, Dividends dropped from the hypothesis set on Trial _i_. Category state change can be similarly defined for the Trial _i_ to Trial _i_+1 transition. Average category state transition recall was computed as a function of the category state transition from Trial _i_-1 to Trial _i_ and as a function of the state transition from Trial _i_ to Trial _i_+1.

The relationship between category recall and subjects hypothesis changes on presolution trials is shown in Figure 5. Note, that the same recall data were used to obtain the two transition patterns. The percent category recall enhancement scores were obtained as the difference between the category recall on Trial _i_ to the average category recall on Session 1 to factor out text saliency effect. These scores were computed separately for learners and nonlearners.

Insert Figure 5 about here

An analysis of variance was performed on recall enhancement scores using three factors: Subject type (learners and non-learners), hypothesis state transitions, and trials transitions (Trial _i_-1 to Trial _i_ and Trial _i_ to Trial _i_+1). This analysis indicated two interactions: Subjects by hypothesis state transitions, $F(3,90)=5.16$, and a hypothesis state transitions by trial transitions, $F(3,90)=3.56$. The first interaction primarily reflects a recall advantage in the Kept and Nonselected states for learners. The second demonstrates a recall increase for the Kept and Dropped state in Trial _i_ to Trial _i_+1 transition.

There are several interesting differences between learners and nonlearners in Figure 5. Consistent with hypothesis data, we show in a different way that the set monitored includes categories that are not yet selected to be in the hypothesis set, as well as those already in it, as evident from their superior recall of the Kept and Nonselected state categories compared to nonlearners. Nonlearners recall is less constructive, reflecting their concern with the last category selection operation and the categories about to be dropped from the hypothesis set. This could imply that nonlearners use less effective hypothesis selection and testing strategies than learners. Nonlearners invest more resources in the operations of selecting and dropping hypotheses on each trial, resulting in better memory for those categories because of the extra processing. As we shall see, the questionnaire data support such an explanation.

Strategy Analysis

Successful performance in any concept identification task relies on the utilization of an appropriate strategy. Since Bruner, Goodnow, and Austin (1956), considerable evidence has accumulated on the appropriate strategy for problems which are simpler but isomorphic to the underlying structure of the task used in this experiment and on the relationship between strategy and overall performance (Laughlin, 1973). Despite the complexities of the task confronting subjects in this experiment, it is appropriate to search for the strategies subjects used and to determine whether they played any role in the distinction between learners and nonlearners.

Instructions to subjects encouraged purposeful, conscious, testing of hypothesis about the categories relevant to Buy/not Buy decisions. The task requires the subject to analyze each text into separate categories of information and to evaluate at least those categories which are pertinent to the current basis of decision (hypothesis). If subjects adopt some detectable strategy, analytic or otherwise, it would have implications not only for speed of learning, but also for the nature of subjects search through categories of information within each text and for the subjects' recall of text.

One way to detect the subject's strategy is to examine the relationships that exist from trial to trial among hypothesis statements. We preferred, however, to use a strategy measure as independent of the primary task as possible. Therefore, we administered a questionnaire to all subjects at the end of the

experiment designed to reveal what, if any, strategy was used. The responses of subjects on this questionnaire indicated, rather clearly, four types of strategies. This classification system is not exactly like any other reported in the literature, but contains within it strategies which have been identified by Levine (1975), among others, in related tasks. We label these strategies as follows. First, A Global strategy similar to Bruner, Goodnow and Austin's Wholistic strategy or what Levine called Global focusing or Perfect processing. There are four subjects who qualify as this type. These are subjects who, from the outset, considered all six categories of information potentially relevant. They kept track of values in each category over successive texts until a category was identified as irrelevant. They attempted logically to eliminate categories on the basis of inconsistencies between category values and changes in the stock's price. Second, a strategy adopted by 22 subjects which we call Focusing. These subjects exhibit a pattern of performance similar to Bruner, Goodnow and Austin's Partist strategy. Their technique is to evaluate only two categories of information in each text, the two they had (sometimes arbitrarily) selected for their hypothesis. They are guided primarily by information in the text just preceding the current trial. They were locally consistent in their hypothesis, but often made inconsistent hypothesis selections relative to information given earlier in the trial sequence.

Each of these two strategies is highly analytic in its orientation. The subject enters each trial with some hypothesis,

reads the text in the light of that hypothesis, assigns information to categories contained within the hypothesis, evaluates those categories, makes a decision on the basis of the evaluation, and changes the hypothesis in the light of feedback received.

The remaining subjects were distinctly different in their orientation toward the task. We refer to one group of 8 subjects as Intuitive. Their decisions tended to be influenced by the overall atmosphere of the text more than by their own hypotheses. They reported difficulty in categorizing the textual information and in dealing with the uncertainty in the task. As a consequence they tended to rely on an overall impression of the paragraphs, positive or negative, as a basis of decision. Their hypotheses were formulated independently of feedback. The final group of 2 subjects is referred to as Unsystematic. They reported being overwhelmed by the task. They did not attempt to categorize textual information and therefore performed no evaluation of category information. Their responses were often described as guesses.

This strategy analysis was made entirely on the basis of the questionnaire data. However, the system of classes that results has implications for performance within the decision task itself, and a series of analyses was undertaken to examine these implications. An obvious prediction holds for the learning data. As noted above, the task requires an analytical orientation. We therefore, expect subjects who adopt an analytic strategy to perform significantly better than subjects who adopt an

intuitive strategy. For purposes of this analysis, we group Global and Focusing subjects (n=26) as analytic in orienation, and Intuitive plus Unsystematic (n=10) as intuitive in orientation. The groups were further divided as to whether they met the criterion of learning. Seventeen analytic subjects but only 2 intuitive subjects met the criterion, resulting in a significant $\chi^2(1)=5.97$. Thus, clearly, subjects who reported following an analytic strategy throughout the learning sessions were more likely to perform successfully on the task itself.

Perhaps the most important implications of the strategy analysis pertain to recall. We examined the following possibility. Subjects should perform well on recall of a given category of information to the extent that they process that category deeply during reading. Subjects will process to the depth of available resources any category of information which is presently a part of their stated hypothesis or otherwise under consideration as a potential determiner of the stock price. If the subject is focusing during presolution trials on certain categories of information to the exclusion of others, recall across categories will have high variability. If the subject considers all categories equally viable, variation in category recall will be low. Because they process two categories of information deeply and the remainder on a shallow level at best, subjects who focus should exhibit high variability in category recall. Subjects in the Intuitive group should show relatively low variability. A critical aspect of our prediction is the Global group. These subjects begin by considering all categories as equally relevant. Therefore, category recall should be low in variability on early

trials. But these subjects also narrow, by a process of elimination from six categories to the relevant two. At that point, recall should be as variable as that exhibited by the Focus group. We expect, then, that category variability and recall will increase significantly over presolution trials for Global subjects. It is difficult to know how unsystematic subjects might perform and our predictions exclude this group.

Figure 6 shows the standard deviation of category recall for the Global, Focus, and Intuitive groups during Vincentized halves of presolution trials. These standard deviations are expressed as difference scores, correcting for variability in Session 1. All groups show an increase in variability, attributable to the increase in overall recall from first to second half of trials. Focus subjects have significantly higher variability than Intuitive subjects. In contrast, Global subjects performed during the first half more like Intuitive subjects and during the second half more like Focus subjects. The statistical test reflecting this interaction is significant, $\underline{F}(1,26)=7.06$.

Insert Figure 6 about here

Tentative and fragmentary though they may be, these data suggest the need for two distinct models to account for problem solving-decision making performance. One reflects a deliberate, hypothesis testing approach to the extraction of information from text and the other reflects a more passive approach driven by the overall atmosphere created by a report (e.g., Hammond, Note 4).

The following is a sketch of a model for analytic subjects (Model I). The subject enters each trial and reads each passage with a control schema which accepts information pertinent to *c* categories. For subjects whom we have referred to as Focussers, *c*=2; for subjects who fall into the Global category, *c* is the total number of categories, here six. In principle, however, subjects may record information about any number of categories. Upon presentation of the text passage, the subject reads to identify information pertinent to the *c* categories of the schema. There is uncertainty at this point, however, for we know that the sentences are not perfectly categorizable. Once the information has been categorized, subjects process further the information in each of their critical categories for evaluation. On the basis of category evaluation, the subject makes a decision (Buy/not Buy) and receives feedback. Feedback is processed in such a way as to correct the current control schema for the next trial. Feedback confirms the viability of some categories and infirms others. Confirmed categories remain a part of the schema for the next trial. Infirmed categories are deleted. This process cycles over successive passages until sufficient information is accumulated to override uncertainty in the category and evaluation processes and to bring the subject to the accurate identification of the two relevant categories of information.

A different model is required for those subjects who used an impoverished control schema in this task (Model II), the intuitive subjects (Hammond, Note 4). These subjects enter a

trial without a hypothesis. They bypass the information categorization stage, moving directly to evaluation. Their evaluation reflects the overall tone of what has been read rather than the value of each sentence, ignoring the implications of feedback for their decision.

There are a number of implications of these two models. Model II subjects might show serial order effects both in recall and decision performance. The value of early and (especially) late categories in a given text ought to have more impact on overall text evaluation and therefore on decision. Model I subjects should show little or no serial order effects on decisions to the extent that $\underline{c}$ is small. Further, Model II subjects should read and make decisions more rapidly because they require fewer processing steps to arrive at a decision point. Finally, the hypothesis statements of Model II subjects should be far less effected by feedback from preceding trials than hypotheses given by Model I subjects. There are probably other implications of these models which will appear as we work them out in detail. But the data of the present experiment are too few to make assessments at the present time.

General Discussion

This research is exploratory. Our purpose was to provide a framework, however sketchy, which would be useful as a general model for information analytic behaviors in complex, naturalistic environments. Our goal was to outline a model, anchored in empirical evidence, which would provide a basis for further, theory-guided research. Such a model requires, at a minimum,

integration of more limited theories of text comprehension, abstraction, and decision making.

The present experiment makes some progress toward this goal. The data show, among other things, that there is a sensible interface between the text comprehension ideas of Kintsch and van Dijk (1978) and the well-worked-out notions of hypothesis behavior (Levine, 1975), which have heretofore been limited in their application to rather simple and artificial conceptual tasks. Indeed, one of the most striking outcomes of the present research is data to establish the greater generality of hypothesis testing notions.

The outstanding characteristic of all of analyses was the great variability among individuals. Despite common instructions and common task requirements, our subjects differed widely in the strategies they used to identify or abstract the relevant categories of information from the texts. While the task itself requires a subject to deal analytically with the text and the majority of subjects did adopt an analytic strategy, a considerable range of approaches from near optimal to entirely intuitive was observed. Furthermore, differences in abstraction strategy correlated with differences in recall performance. Where the subject's strategy called for category processing, e.g. hypothesis testing the relevance of a given category, recall was high. Categories excluded from subject's hypothesis, and therefore presumably not processed as deeply in that particular text were recalled relatively poorly. As another example, consider the high recall of sentence connectives by

nonlearners. This indicates that nonlearners were using a different control schema in reading these texts than the learners, one that probably was not very well defined, but that was more determined by the properties of the text itself than by the decision task. The latter, as we have seen, controlled the reading of the learners. As far as the model of Kintsch and van Dijk (1978) is concerned, the nature of the processes employed by the learners and nonlearners in this task may very well have been the same, but the outcome was very different because of the different control schemata used by these two groups of subjects.

We can conclude at this juncture that individual differences must be part of any general model of information processing. To the extent that these differences can be traced through a variety of performance components, comprehension-recall-abstraction-decision, they become critical in the development of any theoretical framework for understanding information-analytic behavior.

We suspect that the eventual framework, whatever the details, will be schema based. If one accepts this idea, then it becomes possible to investigate some additional interesting empirical questions. There are many ways to learn in this task, that is, to transform the initial task-schema, established by the experimental instructions, into the desired decision schema. What are the most effective ways? Which hypothesis selection and testing strategies succeed, and which fail? What sort of

information does the learner remember from reading the texts, and what do the nonlearners remember? How does text processing and memory relate to the concept learning strategies subjects employ? Tentative answers to these questions have been suggested above, but we plan further experiments to obtain more conclusive evidence.

Eventually, we hope that the kind of results we have obtained will provide a conceptual basis for the development of training procedures in information analysis tasks. Before that is possible, however, we need to investigate longer texts that provide the kind of informational overload that characterizes natural information-analytic tasks. We need to investigate redundant and contradictory texts requiring more complex control schemata and inferential processes. Finally, we need to go beyond the restrictions imposed by a simple deterministic decision rule. It is not at all clear that in more complex tasks the same strategies will be optimal. But we have here, at the very least, developed a method with which we can find out.

Footnote

This research was supported by a contract from the Office of Naval Research, N00014-78-C-0433. This report is publication Number 89 from the Institute of Intellectual Studies at the University of Colorado. Requests for reprints should be sent to Ely Kozminsky, Department of Psychology, University of Colorado, Boulder, Colorado, 80309.

1. A significance level of .05 is assumed hereafter.

2. The microprocesses have been completely formalized in terms of a computer program in Miller and Kintsch (Note 3). No such formalization exists as yet for the other parts of the theory; the application of the macro-operators is intuitive, though constrained by the principles presented in Kintsch and van Dijk (1978).

Reference Notes

1. Kozminsky, E., Bourne, L. E., Jr. & Kintsch, W. Comprehension and analysis of information in text: I. Construction and evaluation of brief texts. Technical Report No. 82-ONR, Institute for the Study of Intellectual Behavior, University of Colorado, Boulder, July, 1979.

2. Spear, T. L. Display Terminal Experiment System User's Manual. CLIPR Publication No. 12, Computer Laboratory for Instruction in Psychological Research, Department of Psychology, University of Colorado, Boulder, 1975.

3. Miller, J. R. & Kintsch, W. Readability and recall of short prose passages: A theoretical analysis. Unpublished manuscript, University of Colorado, 1979.

4. Hammond, K. R. The Unification of Psychological Decision Theory and Social Judgment Theory. Unpublished manuscript, Human Judgment Center, Institute of Behavioral Science, University of Colorado, 1979.

References

Bourne, L.E., Jr. Hypotheses and hypothesis shifts in classification learning, Journal of General Psychology, 1965, 72, 251-261.

Bruner, J.S., Goodnow, J.J., & Austin, G.A. A study of thinking. New York: Wiley, 1956.

Kintsch, W. The representation of meaning in memory. Hillsdale, N.J.: Erlbaum, 1974.

Kintsch, W., & van Dijk, T.A. Toward a model of text comprehension and production. Psychological Review, 1978, 85, 363-394.

Laughlin, P.R. Selection strategies in concept attainment. In R.L. Sols. (Ed.), Contemporary issues in cognitive psychology. Washington, D.C.: Winston, 1973.

Levine, M. A cognitive theory of learning. Hillsdale, N.J.: Lawrence Erlbaum, 1975.

Millward, R.B., & Spoehr, K.T. The direct measurement of hypothesis sampling strategies. Cognitive Psychology, 1973, 4, 1-38.

Rumelhart, D.E., & Ortony, A. The representation of knowledge in memory. IN R.C. Anderson, R.J. Spiro, & W.E. Montague (Eds.) Schooling and the acquisition of knowledge. Hillsdale, N.J.: Erlbaum, 1977.

Spilich, G. J., Vesonder, G. T., Chiesi, H. L., & Voss, J. F. Text processing of domain-related information for individuals with high and low domain knowledge. *Journal of Verbal Learning and Verbal Behavior*, 1979, *18*, 275-290.

Turner, A., & Green, E. The construction of a propositional text base. *JSAS Catalog of Selected Documents in Psychology*, August, 1978.

Table 1

Sample paragraph used in the experiment

The company has skipped the dividend again this year advancing cash flow problems as the cause. Furthermore, banks have refused to renew the company's credit line without representation on the Board of Directors. However, recent strengthening in the monthly composite of leading indicators provides an appearance of a better underlying tone to the economy and company sales could reach $420-440 million, up 25% from the last fiscal year. But, considering the higher prospective shipment costs, earnings can fall in the range of $6.00-$7.00 per share next year rather than the previously estimated $7.00-$8.00. Thus, we anticipate a period of slower growth next year between 3-4% per annum.

Table 2

Proportion correct decisions of learners as a function of solution state and of nonlearners as a function of sessions

	Solution State		
	Before solution	After Solution	Mean
Learners	.46	.73	.60
	First two sessions	Last two sessions	
Nonlearners	.53	.53	.53
Mean	.50	.63	.56

Table 3

Presolution hypotheses selection characteristics of learners and nonlearners

(a) Probability of hypothesis change per trial.

	First Half	Second Half	Mean
Learners	.59	.35	.47
Nonlearners	.55	.32	.44
Mean	.57	.34	.46

(b) Average number of category changes per hypothesis change.

	First Half	Second Half	Mean
Learners	1.40	1.08	1.24
Nonlearners	1.21	1.13	1.17
Mean	1.30	1.11	1.20

(c) Proportion of incorrect decisions in a hypothesis run.

	First Half	Second Half	Mean
Learners	.65	.62	.64
Nonlearners	.49	.67	.58
Mean	.57	.65	.61

(d) Probability of changing a hypothesis after an error.

	First Half	Second Half	Mean
Learners	.74	.97	.86
Nonlearners	.60	.83	.72
Mean	.67	.90	.79

(e) Proportion of hypothesis recurrences to number of hypotheses changes.

	First Half	Second Half	Mean
Learners	.18	.47	.32
Nonlearners	.39	.54	.46
Mean	.28	.50	.39

(f) Average trials distance between hypotheses repetition.

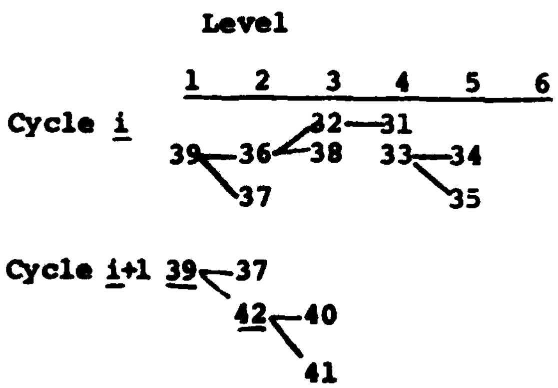
	First Half	Second Half	Mean
Learners	4.10	8.20	6.15
Nonlearners	3.55	5.42	4.48
Mean	3.82	6.81	5.32

Table 4

The processing of a sample sentence from the text example in Table 1

SENTENCE		THEORY:	PERCENT RECALL: PREDICTED	OBSERVED
31	(BUT,P32)	S	16	14
32	(CONSIDERING, P33, P36)	S	16	25
33	(HIGHER, COST)	S	16	25
34	(SHIPMENT, COST)	S	16	35
35	(PROSPECTIVE, COST)	S	16	0
36	(CAN, P37)	S	16	8
37	(RANGE, EARNINGS, \$6-7PSH)	SSMN	79	83
38	(NEXT-YEAR, P36)	S	16	0
39	(RATHER-THAN, P37, P42)	SSSMN	82	83
BREAK AFTER 21 WORDS				
40	(PREVIOUSLY, P41)	S	16	25
41	(ESTIMATED, P42)	S	16	50
42	(RANGE, EARNINGS, \$7-8PSH)	SSMN	79	83
SENTENCE				
⋮				

Processing Cycle Text Base:



MACRO PROCESSES:
Cue-word "EARNINGS"
Selects P37, P42;
Add P39 as connective

Table 5

Goodness of fit of the model

for the four experimental texts

Summary for S-2:

Text:	χ^2	df	p	m	n	r	r^2
A	46.51	36	.30	.86	.68	.81	.66
B	18.54	20	.22	.44	.00	.84	.71
C	22.75	21	.27	.80	.00	.87	.76
D	27.94	19	.16	.70	.31	.83	.69
	115.74	96	.24	.70	.25	.84	.71

Figure Captions

1. The proportion of subjects who identified correctly the categories Growth (full line), Earnings (broken line), and both Growth and Earnings (dotted line) on the 20 experimental problems and the final test.

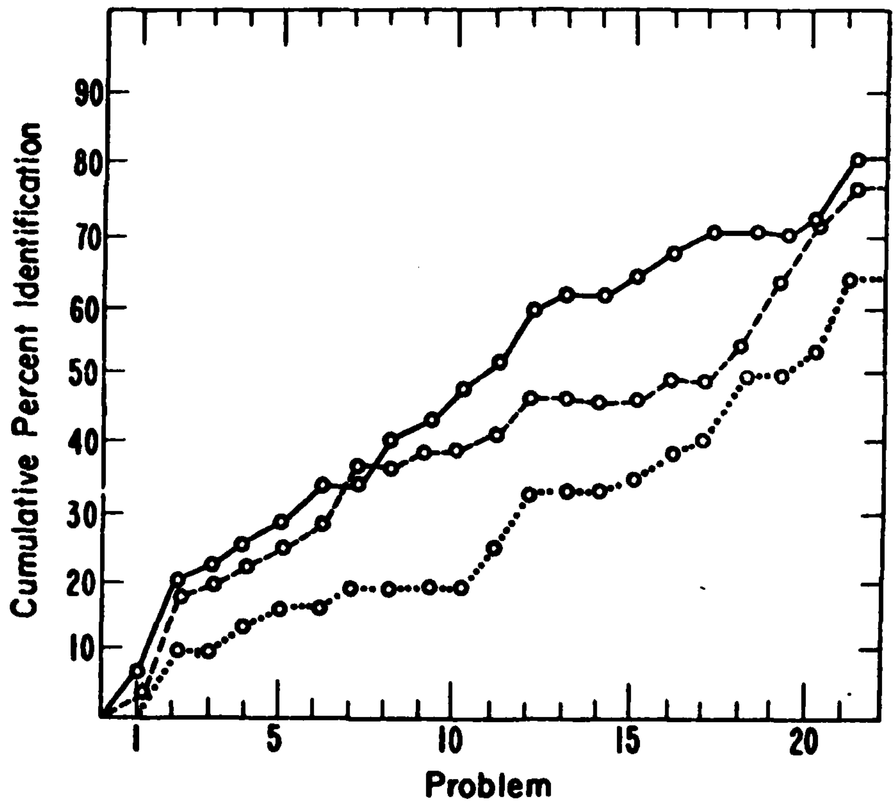
2. The proportion of correct decisions for learners (full line) and nonlearners (broken line) for the four experimental sessions.

3. Improvement in recall of the relevant sentences on pre- and post-solution trails. The dotted line indicates the 95% confidence interval.

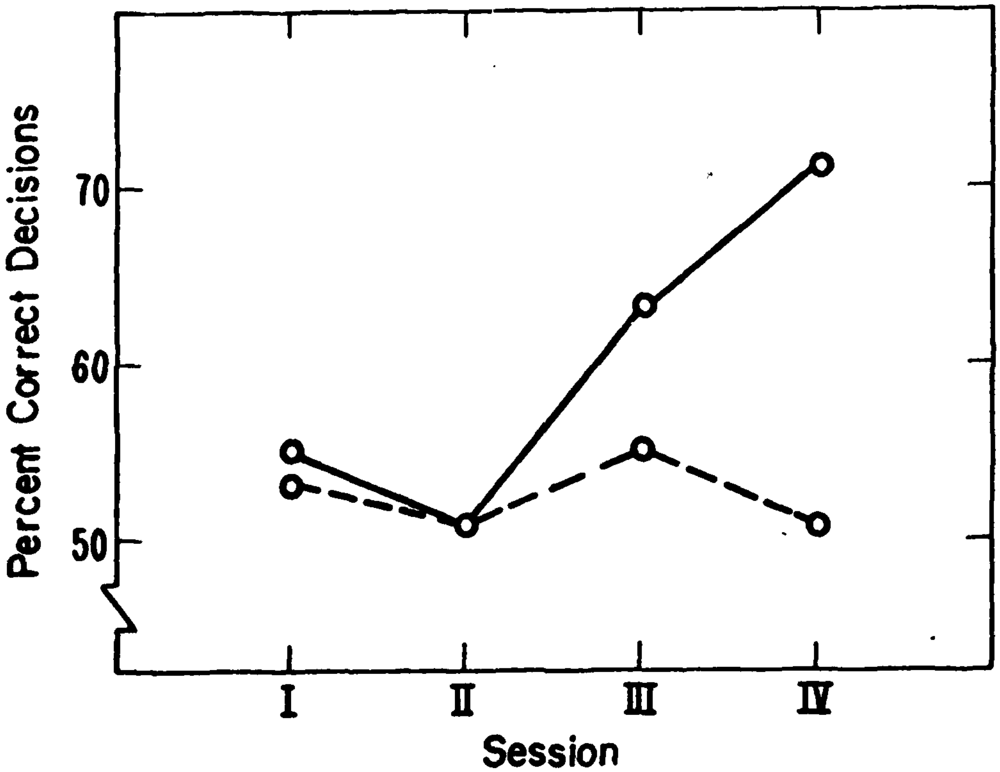
4. Improvement in recall over the four experimental sessions for irrelevant sentences (broken line, open circles), relevant sentences-unlearned (broken line - full circles), and relevant sentences-learned (full line).

5. The relationship between category recall and hypothesis changes on presolution trials for learners (shaded bars) and nonlearners (unshaded bars).

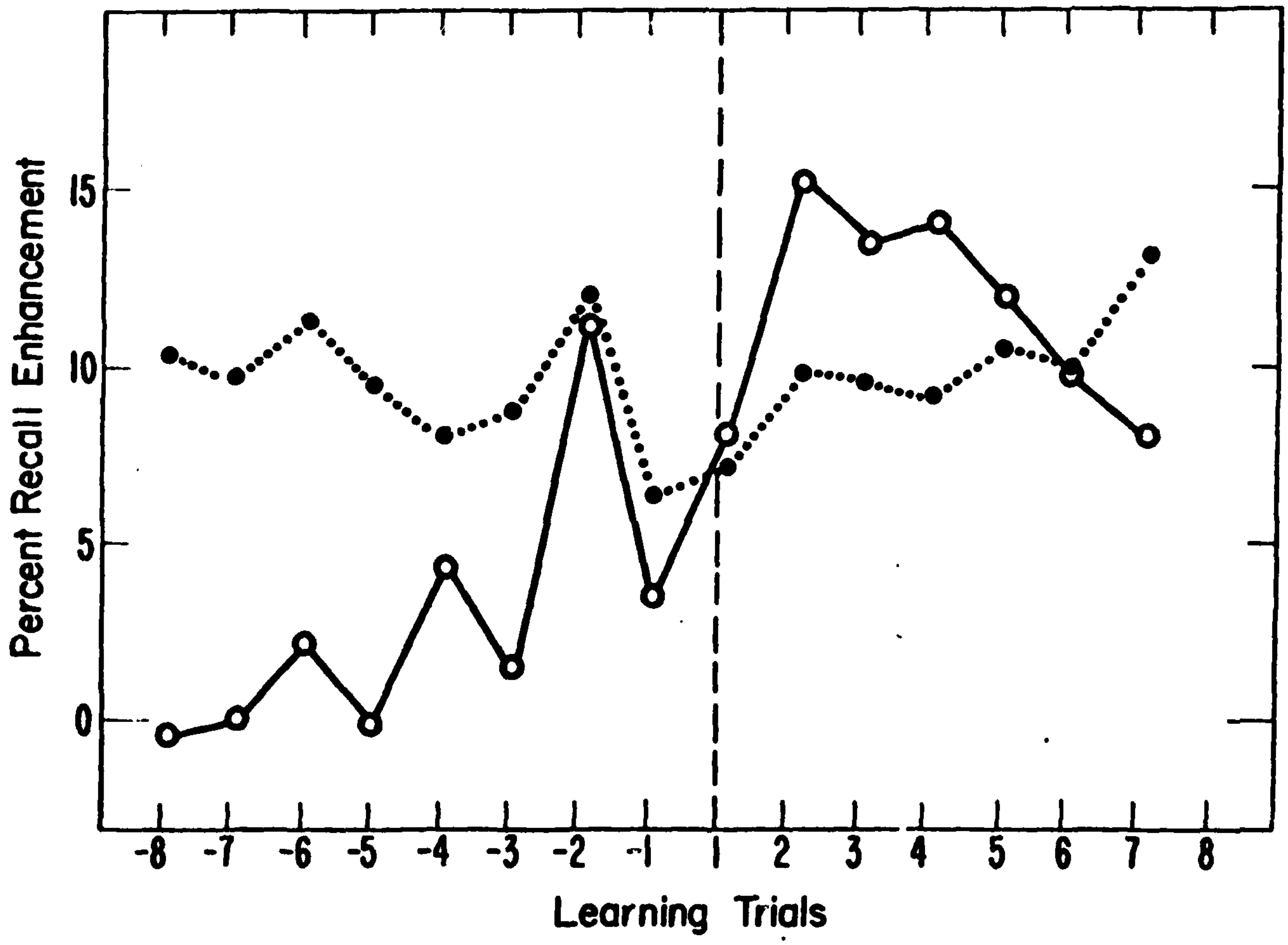
6. The variability in category recall on presolution trials for Global (closed circles), Focus (open circles) and Intuitive (squares) subjects.

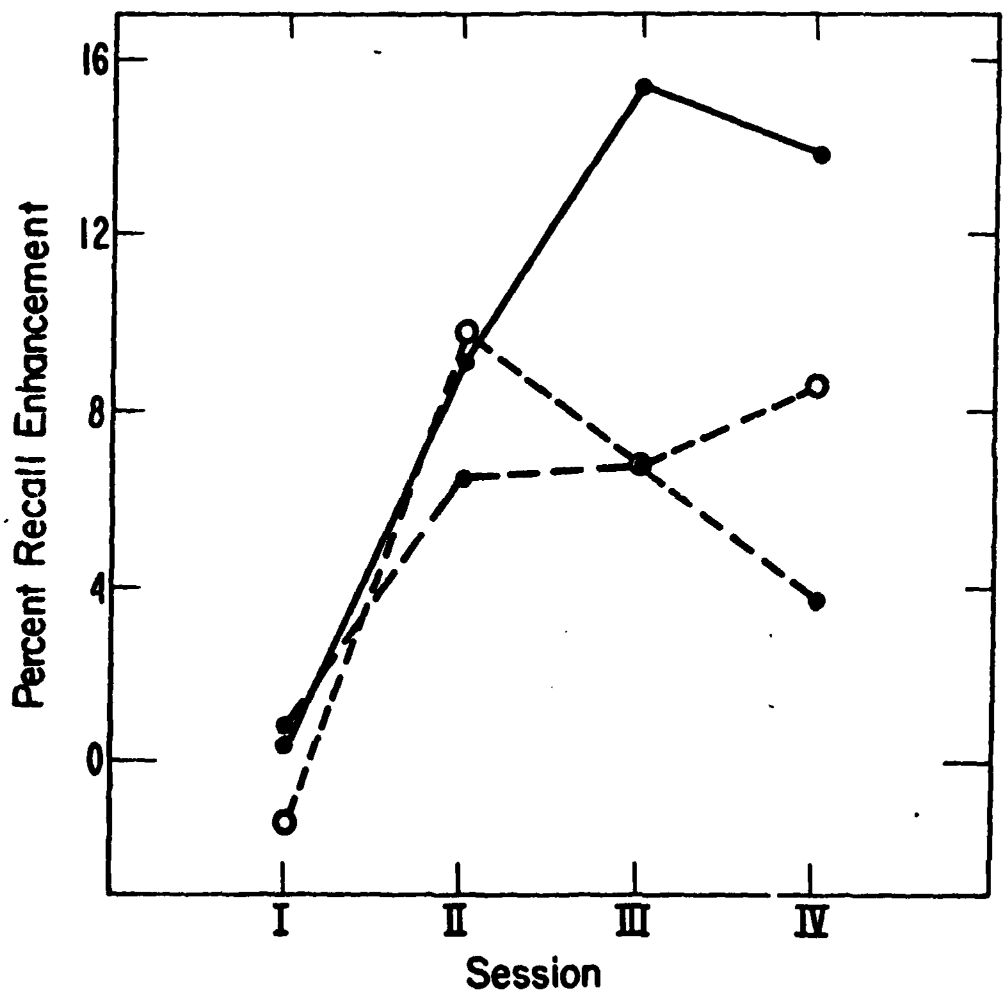


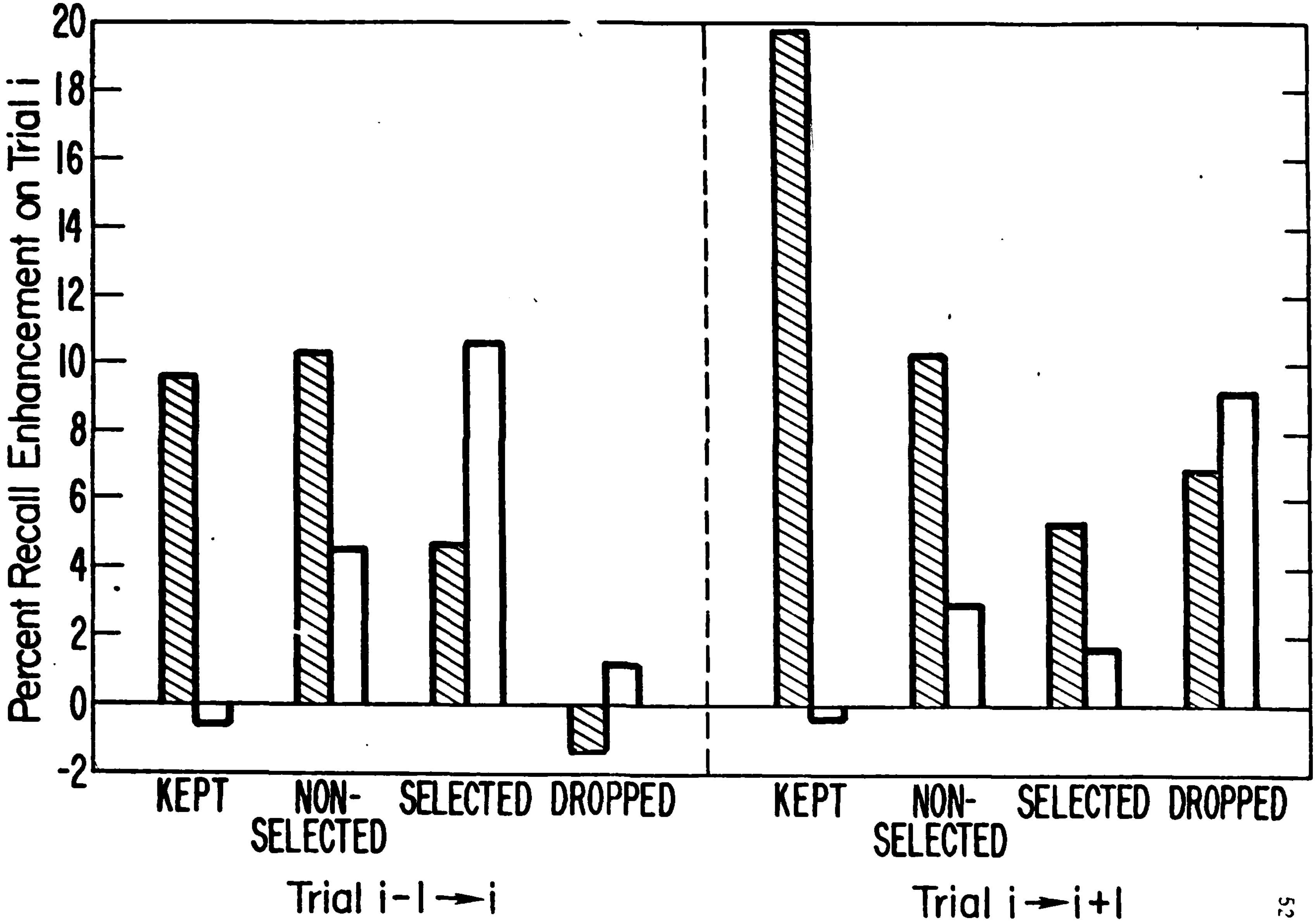
Cumulative Percent Identification
90
80
70
60
50
40
30
20
10
1
5
10
15
20
Problem

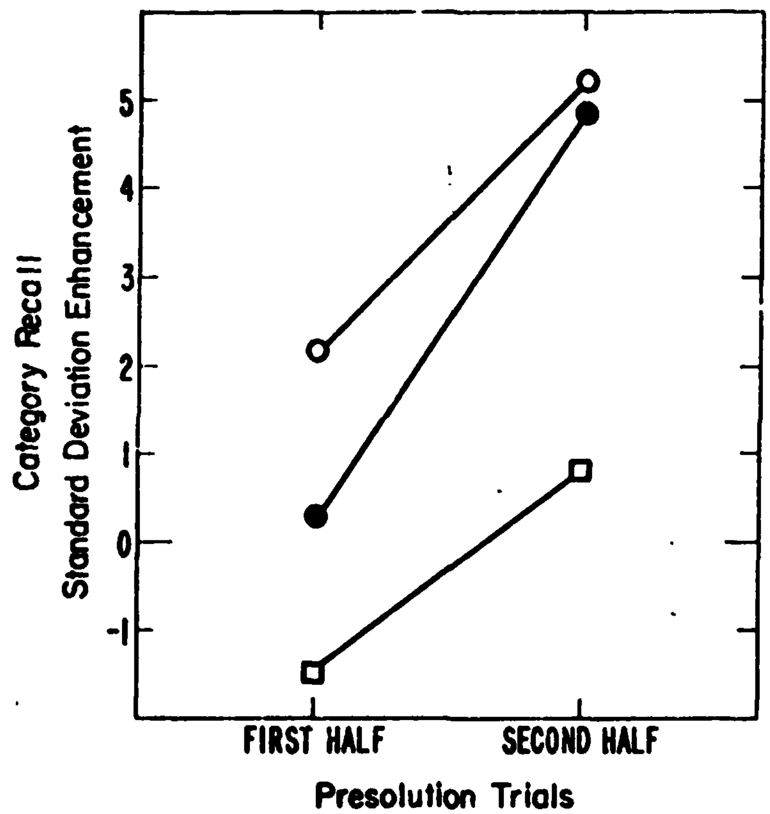


Percent Correct Decisions
70
60
50
I
II
III
IV
Session


Percent Recall Enhancement
15
10
5
0
-8 -7 -6 -5 -4 -3 -2 -1 1 2 3 4 5 6 7 8
Learning Trials


16
12
8
4
0
Percent Recall Enhancement
I
II
III
IV
Session


Percent Recall Enhancement on Trial i
20
18
16
14
12
10
8
6
4
2
0
-2
KEPT
NON-SELECTED
SELECTED
DROPPED
KEPT
NON-SELECTED
SELECTED
DROPPED
Trial i-1 → i
Trial i → i+1


Category Recall
Standard Deviation Enhancement
5
4
3
2
1
0
-1
FIRST HALF
SECOND HALF
Presolution Trials

Navy

1 Dr. E. Aiken
Navy Personnel Research & Development Center
San Diego, CA 92152

1 Dr. Jack R. Borsting
Provost & Academic Dean
U. S. Naval Postgraduate School
Monterey, CA 93940

1 Dr. Robert Breaux
Code N-71
NAVTRAEQUIPCEN
Orlando, FL 32813

1 Dr. Charles E. Davis
ONR Branch Office
536 S. Clark Street
Chicago, IL 60605

1 Mr. James S. Duva
Chief, Human Factors Laboratory
Naval Training Equipment Center
(Code N-215)
Orlando, Florida 32813

1 Dr. Richard Elster
Dept. of Administrative Sciences
Naval Postgraduate School
Monterey, CA 93940

1 Dr. Pat Federico
Navy Personnel R & D Center
San Diego, CA 95152

1 Dr. John Ferguson, MSC, USN
Naval Medical R&D Command (Code 44)
National Naval Medical Center
Bethesda, MD 20014

1 Dr. John Ford
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Eugene Gloye
ONR Branch Office
1030 E. Green Street
Pasadena, CA 91101

1 Dr. Steve Harris
Code L522
NAMRL
Pensacola, FL 32508

1 LCDR Charles W. Hutchins
Naval Air Systems Command
444 Jefferson Plaza #1
Jefferson Davis Highway
Arlington, VA 20360

1 Dr. Norman J. Kerr
Chief of Naval Technical Training
Naval Air Station Memphis
Millington, TN 38054

1 Dr. Leonard Kroeker
Navy Personnel R&D Center
San Diego, CA 95152

1 Chairman, Leadership & Law Dept.
Div. of Professional Development
U.S. Naval Academy
Annapolis, MD 21402

1 Dr. James Lester
ONR Branch Office
Bldg. 114, Sec. D
666 Summer Street
Boston, MA 02210

1 Dr. William L. Maloy
Principal Civilian Advisor for Education and Training
Naval Training Command, Code 00A
Pensacola, FL 32508

1 Capt. Richard L. Martin
USS Francis Marion (LPA-249)
FPO New York, NY 09501

2 Dr. James McGrath
Navy Personnel R&D Center
Code 306
San Diego, CA 95152

1 Dr. William Montague
LRDC
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

1 Commanding Officer
U. S. Naval Amphibious School
Coronado, CA 92155

1 Commanding Officer
Naval Health Research Center
Attn: Library
San Diego, CA 95152

1 Naval Medical R&D Command
Code 44
National Naval Medical Center
Bethesda, MD 20014

1 Capt. Paul Nelson, USN
Chief, Medical Service Corps.
Code 7
Bureau of Medicine & Surgery
U.S. Dept. of the Navy
Washington, DC 20372

1 Library
Navy Personnel R&D Center
San Diego, CA 95152

6 Commanding Officer
Naval Research Laboratory
Code 2627
Washington, DC 20390

1 John Olsen
Chief of Naval Education & Training Support
Pensacola, FL 32509

1 Psychologist
ONR Branch Office
495 Summer Street
Boston, MA 02210

1 Office of Naval Research
Code 200
Arlington, VA 22217

1 Office of Naval Research
Code 437
800 N. Quincy Street
Arlington, VA 22217

5 Personnel & Training Research Programs
(Code 458)
Office of Naval Research
Arlington, VA 22217

1 Psychologist
Office of Naval Research Branch
223 Old Marylebone Road
London, NW, L5th, England

1 Psychologist
ONR Branch Office
1030 East Green Street
Pasadena, CA 91101

1 Scientific Director
Office of Naval Research
Scientific Liaison Group/Tokyo
American Embassy
APO San Francisco, CA 96503

1 Head, Research, Development & Studies (OP102X)
Office of the Chief of Naval Operations
Washington, DC 20370

1 Scientific Advisor to the Chief of Naval Personnel (PERS-OR)
Naval Bureau of Personnel
Room 4410, Arlington Annex
Washington, DC 20370

1 Mr. Arnold Rubenstein
Naval Personnel Support Technology
Naval Material Command (08T244)
Room 1044, Crystal Plaza #5
2221 Jefferson Davis Highway
Arlington, VA 20360

1 Dr. Richard Pollack
Academic Computing Center
U.S. Naval Academy
Annapolis, MD 21402

1 Dr. Worth Scanland
Chief of Naval Education & Training
Code N-5
NAS, Pensacola, FL 32508

1 A. A. Sjoholm
Tech. Support, Code 201
Navy Personnel R&D Center
San Diego, CA 96152

1 Mr. Robert Smith
Office of Chief Naval Operations
OP-987E
Washington, DC 20350

1 Dr. Alfred F. Smode
Training Analysis & Evaluation
Group (TAEG)
Department of the Navy
Orlando, FL 32813

1 CDR Charles J. Theisen, Jr.
MSC, USN
Head, Human Factors Eng. Div.
Naval Air Development Center
Warminster, PA 18974

1 W. Gary Thomson
Naval Ocean Systems
Code 7132
San Diego, CA 96152

Army

1 ARI Field Unit-USAREUR
Attn: Library
C/O ODCSPER
HQ USAREUR & 7th Army
APO New York, NY 09403

1 Technical Director
U.S. Army Research Institute for
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 HQ USAREUE & 7th Army
ODCSOPS
USAAREUE Director of GED
APO New York, NY 09403

1 Dr. Ralph Dusek
U. S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Ed Johnson
Army Research Institute
5001 Eisenhower Blvd.
Alexandria, VA 22333

1 Dr. Michael Kaplan
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Milton S. Katz
Individual training & Skill
Evaluation Technical Area
U. S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Harold F. O'Neil, Jr.
Attn: PERI-OK
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Director, Training Development
U.S. Army Administration Center
Attention: Dr. Sherrill
Ft. Benjamin Harrison, IN 46218

1 Dr. Joseph Ward
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Air Force

1 Dr. G. A. Eckstrand
AFHRL/AS
Wright-Patterson AFB, OH 45433

1 Dr. Mercer
CNET Liaison Office
AFHRL/Flying Training Division
Williams AFB, AZ 85224

1 Research Branch
AFMPC/DPMYP
Randolph AFB, TX 78148

1 Dr. Marty Rockway (AFHRL/TT)
Lowry AFB
Denver, CO 80230

1 Jack A. Thorpe, Capt., USAF
Program Manager
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332

1 Brian K. Waters, LCol., USAF
Air University
Maxwell AFB
Montgomery, AL 36112

Other DoD

1 Dr. Stephen Andriole
Advanced Research Projects Agency
1400 Wilson Blvd.
Arlington, VA 22209

12 Defense Documentation Center
Cameron Station, Bldg. 5
Alexandria, VA 22314
Attn: TC

1 Dr. Craig Fields
Advanced Research Projects Agency
1400 Wilson Blvd.
Arlington, VA 22209

1 Dr. J. Dexter Fletcher
Advanced Research Projects Agency
1400 Wilson Blvd.
Arlington, VA 22209

1 Military Assistant for Training and
Personnel Technology
Office of the Under Secretary of
Defense for Research & Engineering
Room 3D129, The Pentagon
Washington, DC 20301

Civil Government

1 Dr. Susan Chipman
Basic Skills Program
National Institute of Education
1200 19th Street, NW
Washington DC 20208

1 Dr. A. Fields
Central Intelligence Agency
1820 N. Fort Myer
Arlington, VA 22209

1 Dr. Joseph I. Lipson
Division of Science Education
Room W-638
National Science Foundation
Washington, DC 20205

1 Dr. Joseph Markowitz
Office of Research and Development
Central Intelligence Agency
Washington, DC 20205

1 Dr. John Mays
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Andrew R. Molnar
Science Education Dev.
and Research
National Science Foundation
Washington, DC 20550

1 Dr. H. Wallace Sinaiko
Program Director
Manpower Research & Advisory Serv.
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

1 Dr. Thomas G. Sticht
Basic Skills Program
National Institute of Education
1200 North 19th Street NW
Washington, DC 20208

1 Dr. Joseph L. Young, Director
Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

Non Government

1 Professor Earl A. Alluisi
Dept. of Psychology
Code 287
Old Dominion University
Norfolk, VA 23508

1 Dr. John R. Anderson
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213

1 Psychological Research Unit
Department of Defense (Army Office)
Campbell Park Offices
Canberra ACT 2600 Australia

1 Dr. Michael Atwood
Science Applications Institute
Denver Tech. Center West
7935 E. Prentice Avenue
Englewood, CO 80110

1 Dr. Perry Beilke
Room 204
Bandelier Hall, W.
University of New Mexico
Albuquerque, NM 87131

1 Dr. Nicholas A. Bond
Department of Psychology
Sacramento State College
600 Jay Street
Sacramento, CA 95819

1 Dr. Kenneth Bowles
Institute for Information Sciences
University of California at San Diego
La Jolla, CA 92037

1 Dr. John S. Brown
Xerox Palo Alto Research Center
3333 Coyote Road
Palo Alto, CA 94304

1 Dr. C. Victor Bunderson
WICAT Inc.
University Plaza, Suite 10
1160 So. State Street
Orem, Utah 84057

1 Charles Myers Library
Livingstone House
Livingstone Road
Stratford, London E15 2LJ
England

1 Dr. William Chase
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213

1 Dr. Micheline Chi
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

1 Dr. Allan M. Collins
Bolt, Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

1 Dr. Meredith Crawford
Dept. of Engineering Administration
George Washington University
2101 L Street, N.W., Suite 805
Washington, DC 20037

1 Dr. Hubert Dreyfus
Department of Philosophy
University of California
Berkeley, CA 94720

1 Major I. N. Evonic
Canadian Forces Pers. Applied
Research
1107 Avenue Road
Toronto, Ontario, Canada

1 Dr. Ed Feigenbaum
Dept. of Computer Science
Stanford University
Stanford, CA 94305

1 Mr. Wallace Feurzeig
Bolt, Beranek & Newman, Inc.
50 Moulton St.
Cambridge, MA 02138

1 Dr. Victor Fields
Dept. of Psychology
Montgomery College
Rockville, MD 20850

1 Dr. Edwin A. Fleishman
Advanced Research Resources Organ.
8555 Sixteenth Street
Silver Spring, MD 20910

1 Dr. John Frederiksen
Bolt, Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

1 Dr. Robert Glaser
LRDC
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

1 Dr. Ira Goldstein
Xerox Palo Alto Research Center
3333 Coyote Road
Palo Alto, CA 94304

1 Dr. James G. Greeno
LRDC
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

1 Dr. Kenneth R. Hammond
Human Judgment Center
Campus Box 485
University of Colorado
Boulder, CO 80309

2 Dr. Barbara Hayes-Roth
The Rand Corporation
1700 Main Street
Santa Monica, CA 90406

1 Library
Humrro/Western Division
27857 Berwick Drive
Carmel, CA 93921

1 Dr. Earl Hunt
Department of Psychology
University of Washington
Seattle, WA 98105

1 Mr. Gary Irving
Data Sciences Division
Technology Services Corporation
2811 Wilshire Blvd.
Santa Monica, CA 90403

1 Dr. Lawrence B. Johnson
Lawrence Johnson & Assoc., Inc.
Suite 502
2001 S. Street, N.W.
Washington, DC 20009

1 Dr. Wilson A. Judd
McDonnell-Douglas
Astronautics Co., East
Lowry AFB
Denver, CO 30203

1 Dr. Arnold F. Kanarick
Honeywell, Inc.
2600 Ridgeway Pkwy
Minneapolis, MN 55413

1 Dr. Steven W. Keele
Department of Psychology
University of Oregon
Eugene, OR 97403

1 Dr. Janice M. Keenan
Department of Psychology
University of Denver
Denver, CO 80208

1 Dr. David Kieras
Department of Psychology
University of Arizona
Tuscon, AZ 85721

1 Mr. Marlin Kroger
1117 Via Goleta
Palos Verdes Estates, CA 90274

1 LCOL C. R. J. Lafleur
Personnel Applied Research
National Defense HQS
101 Colonel By Drive
Ottawa, Canada K1A 0K2

1 Dr. Jill Larkin
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213

1 Dr. Alan Lesgold
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

1 Dr. Robert A. Levit
Manager, Behavioral Sciences
The BDM Corporation
7915 Jones Branch Drive
McLean, VA 22101

1 Dr. Robert R. Mackie
Human Factors Research, Inc.
6780 Cortona Drive
Santa Barbara Research Pk.
Goleta, CA 93017

1 Dr. Mark Miller
Systems and Information Sciences
Laboratory
Central Research Laboratories
Texas Instruments, Inc.
Mail Station 5
Post Office Box 5936
Dallas, TX 75222

1 Dr. Richard Millward
Department of Psychology
Hunter Lab.
Brown University
Providence, RI 02912

1 Dr. Allen Munro
University of Southern California
Behavioral Technology Labs
South Hope Street
Los Angeles, CA 90007

1 Dr. Donald A. Norman
Department of Psychology C-009
University of California, San Diego
La Jolla, CA 92093

1 Dr. Seymour A. Papert
Massachusetts Institute of Technology
Artificial Intelligence Lab
545 Technology Square
Cambridge, MA 02139

1 Dr. James A. Paulson
Portland State University
P.O. Box 751
Portland, OR 97207

1 Mr.Luigi Petrullo
2431 N. Edgewood Street
Arlington, VA 22207

1 Dr. Peter Polson
Department of Psychology
University of Colorado
Boulder, CO 80309

1 Dr. Diane M. Ramsey-Klee
R-K Research & System Design
3947 Ridgemont Drive
Malibu, CA 90265

1 Dr. Peter B. Read
Social Science Research Council
605 Third Avenue
New York, NY 10016

1 Dr. Fred Reif
SESAME
C/o Physics Department
University of California
Berkeley, CA 94720

1 Dr. Allen Schoenfeld
SESAME
C/o Physics Department
University of California
Berkeley, CA 94720

1 Dr. Robert J. Seidel
Instructional Technology Group
HUMRRO
300 N. Washington St.
Alexandria, VA 22314

1 Dr. Richard Snow
School of Education
Stanford University
Stanford, CA 94305

1 Dr. Robert Sternberg
Department of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

1 Dr. Albert Stevens
Bolt, BEranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

1 Dr. Patrick Suppes
Institute for Mathematical Studies
in the Social Sciences
Stanford University
Stanford, CA 94305

1 Dr. John Thomas
IBM Thomas J. Watson Research
Center
P.O. Box 218
Yorktown Heights, NY 10598

1 Dr. Perry Thorndyke
The Rand Corporation
1700 Main Street
Santa Monica, CA 90406

1 Dr. Benton J. Underwood
Department of Psychology
Northwestern University
Evanston, IL 60201

1 Dr. Douglas Vizond
Department of Psychology
St. Thomas University
Fredericton, N.B. E3B 5G3
Canada

1 Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

1 Dr. Karl Zinn
Center for Research on Learning
and Teaching
University of Michigan
Ann Arbor, MI 48104